Using RFID Snapshots for Mobile Robot Self-Localization

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***Abstract*— In recent years, radio frequency identification (RFID) has found its way into the field of mobile robot navigation. On the one hand, the technology promises to contribute solutions to common problems in self-localization and mapping such as the data association problem. On the other hand, questions like how to cope with poor or even missing range and bearing information remain open. In this paper, we present a novel method which tackles these challenges: Inspired by vision-based self-localization approaches, it utilizes RFID snapshots for the estimation of the robot pose. Our experiments show that the new technique enables a robot to successfully localize itself in an indoor environment. The accuracy is comparable to the one of a previous approach using an explicit model of detection probabilities. Our method, however, requires fewer iterations of the underlying particle filter in order to converge to the approximate robot pose.**

***Index Terms*— RFID, mobile robot, self-localization, particle filter**

I. Introduction

The task of robotic self-localization, in which a robot estimates its position in a given map of the environment, has been studied extensively over the past decade. Many solutions have been found, and sensors such as laser scanners or cameras and techniques such as Monte Carlo localization [12] have proven to allow for efficient and robust positioning.

In recent years, radio frequency identification (RFID) has attracted economic, public, and scientific interest. Having found its way into robotics, it promises improvements in self-localization, mapping, and navigation in general. Among the various interesting properties of RFID, the probably most important is that objects equipped with RFID tags can be identified uniquely. Thereby the issue of associating sensor readings to navigation landmarks can be solved trivially. Moreover, tags can be detected without contact and even without the requirement of line-of-sight, since electromagnetic waves can pass through objects. However, many factors can interfere with the transmission of the radio signal, resulting in a high uncertainty of scan results. Another shortcoming is the fact that – at least in the case of passive RFID tags – an RFID reader can only determine whether or not a tag is in its range. Neither distance nor bearing to a recognized label are supplied.

Several strategies to overcome those issues have emerged, of which we give an overview in Section II. In this paper, we present a novel approach in which snapshots of current RFID measurements are taken to localize a mobile robot. In brief, our technique accumulates RFID readings over a short series of measurement cycles. The list of detected tags along with the number of detections is treated as a feature vector which represents a snapshot of the current localization context. Our technique is inspired by vision-based self-localization methods. This family matches global image features taken by the camera of the robot with a database of learned features, which are annotated with the true pose of the robot when the corresponding images were recorded (see e.g. [11]). Analogously, we first learn the snapshots at known positions in a training phase. After that, during normal operation of the robot, we match current snapshots with the memorized features in order to retrieve pose estimates. We finally apply a particle filter (see e.g. [4]) to achieve robustness.

In order to compare our approach with previous ones, we have also implemented the method by Hähnel et al. [5], described in the next section. Our experiments show that the snapshot-based localization technique provides similarly accurate results. It converges, however, considerably faster to the approximate robot pose.

This paper is organized as follows: In Section II, we present a survey of related work, before we give an overview of characteristics inherent to RFID sensors in Section III. Taking advantage of those characteristics, we designed our new snapshot-based localization algorithm, which is introduced in Section IV. We performed a series of experiments with this method, of which the results are presented in Section V. In Section VI, we finally summarize our work and draw conclusions.

II. Related Work

In the last few years, RFID sensors have attracted the attention of researchers into robotics, and a number of approaches have been presented which employ the new technology for different navigation tasks.

One of the first surveys into how to localize a mobile robot via RFID is the one by Hähnel et al. [5]. It is also highly relevant to this paper, because we implemented their method as a benchmark for our approach; note that our robot is equipped with very similar RFID hardware. Hähnel et al. first gained a probabilistic sensor model for their RFID reader, which associates the probability of detecting an RFID tag with the relative position of that tag with respect to the antenna. This model was used to map the positions of passive RFID tags in an office environment, given a previously computed map learned via a laser-based SLAM algorithm. The position of each tag was represented by a number of particles, whose weights were updated after each detection of the tag. Monte Carlo localization was then used to estimate the position of the robot in the map, using another set of particles to represent the robot pose. In experiments, it was possible to achieve robust (albeit rather inaccurate) self-localization based on RFID data and odometry alone. Furthermore, self-localization was greatly accelerated, and the required number of particles could be reduced if the data of laser scanner and RFID reader were combined as compared to localization with a laser scanner only.

A somewhat similar work, originally intended to locate nomadic objects, is the one by Liu et al. [10]. They demonstrated a system for passive UHF tags which exploits the directionality of RFID readers. Beliefs of the positions of tagged objects are formed from varying robot poses over time. Yamano et al. [14] successfully examined how support vector machines could learn robot locations. They generated feature vectors out of signal strength information gained from active RFID tags. A two-step approach to indoor localization was employed by Chae and Han [2]: First they determined a coarse region, computing a weighted sum of the positions of currently detected tags. Then the robot was localized on a finer level by means of monocular vision involving SIFT features. The system relied on active RFID, and the positions of tags, which were attached to walls, had to be known. Djugash et al. [3] utilized active RFID tags in an outdoor environment. They used time-of-flight measurements both for pure self-localization and for simultaneous localization and mapping based on Kalman and particle filters. In the context of passive high frequency (HF) tags operating at 13.56 MHz, Bohn [1] has furthermore examined how tags densely spread on the floor allow for location estimation. Tsukiyama et al. [13] explored a simple navigation mechanism on the basis of vision for free space detection and RFID tags as labels within a topological map of an indoor environment. Navigation based on passive RFID tags has also been studied by Kulyukin et al. [7, 8, 9]. Their robotic guide was able to assist visually impaired people in wayfinding in indoor environments. Kleiner and Nebel et al. [6, 16] studied the use of RFID labels for the coordination of robot teams in exploration, during which the labels were autonomously deployed. Recently, Zhou et al. [15] proposed a vision-based indoor localization method in which they used modified active RFID tags as landmarks. The tags were equipped with bright LEDs to be recognized. An additional laser diode allowed for the selective activation via a laser beam emitted by the robot. A prototype system, which lacked the ability to autonomously point a laser at visually recognized RFID labels, promised accurate localization. Note that the laser activation step requires line-of-sight, which is generally not the case for other RFID-based localization approaches.

III. Characteristics of RFID Sensors

Radio frequency identification systems consist of two types of components: an RFID reader (including a set of antennas) and a number of RFID transponders (tags). The reader can communicate with the tags by means of radio signals and retrieve their ID numbers and in some cases additional information stored on the tags. This general principle can be implemented in several ways, making use of different physical mechanisms. For our work, we use an off-the-shelf reader (Alien Technology ALR-8780) working in the ultra high frequency band (UHF, 868 MHz) with a set of passive tags, i. e. tags without an internal power supply. The reader is compliant to the new UHF standard EPC Class 1 Generation 2 and offers a read range of approximately five meters. The RFID system includes four antennas, forming two sender/receiver pairs. The two antennas of each pair are mounted on one side of our RWI B21 robot, in an angle of 45° with respect to the forward direction (Fig. 1).

Fig. 1. Left: The RWI B21 service robot employed for our studies, equipped with an UHF RFID reader and two pairs of UHF antennas. Right: The type of tag ("squiggle tag") that we used for our studies, manufactured by Alien Technology (drawn to a larger scale than the robot on the left). The size of the tag is approximately 10 cm $\times$ 1 cm.

The reader is able to detect multiple transponders by issuing a series of low-level communication signals in response to a single high-level control command. The detection attempt can also be repeated for a preset number of times, N_{max}. The result of such a scan is a list of transponder IDs, together with the number of successful detections for each transponder and the antenna numbers the detections were performed with. For the self-localization algorithm, the reader response is split up into the scan results for the two antenna pairs. These results give an idea about which transponders can be "seen" from the corresponding antenna position. They are therefore termed *RFID snapshots* in analogy to vision-based navigation approaches. Formally, a snapshot can be written as a vector $\mathbf{f} = (f_1, \ldots, f_k)^T$ of detection frequencies, with one element for each transponder that has been detected so far. The entries f_i are in the range $[0, N_{max}]$. Note that such a vector contains considerably less information than a camera snapshot in vision-based localization. In particular, it does not yield any information regarding the relative positions of the detected transponders. However, the RFID snapshots can be taken and stored at minimal computational cost during normal operations of the robot, and no feature extraction procedures

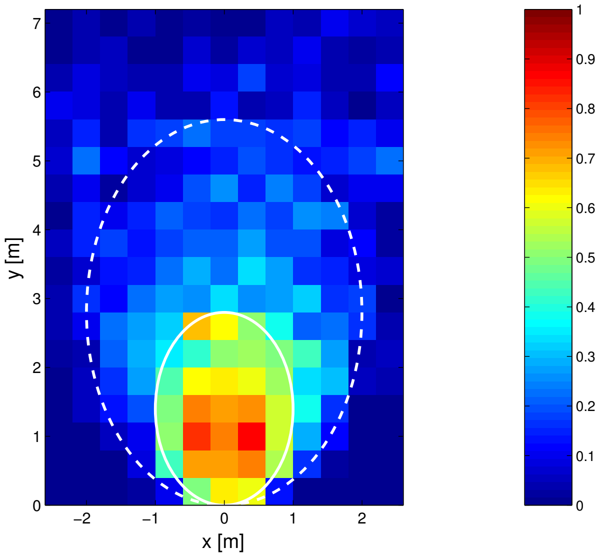

Fig. 2. Detection rates and sensor model. The diagram depicts the detection rates (number of detections per total number of scans) for different transponder positions in the horizontal plane. The RFID antenna is located at the origin of the plot, pointing in the direction of the y-axis. The detection rates were determined from 200 scans for each position, averaged over different heights and orientations of the transponder. The sensor model we used in the implementation of Hähnel's algorithm is superimposed to the plot: The detection probability is modelled to be 0.5 for the area within the inner (solid white) ellipse, 0.2 within the outer (dashed white) ellipse, and 0.05 outside the ellipses.

are required to use them for localization. During the training phase, the snapshots are stored together with the antenna pose they were taken at. The employment of the snapshots for self-localization is described in detail in the next section.

In passive RFID systems working in the UHF band, both the power supply of the transponder and the communication between reader and transponder are achieved by electromagnetic waves emitted from the antennas. To allow the detection of a transponder, i. e. the successful transmission of its ID to the reader, it must receive a sufficiently strong signal from the emitter antenna and a reflected signal must be detected by the reader. Whether a detection occurs depends on many parameters, including the relative position and orientation of the transponder to the antenna, the material the transponder is attached to, and obstacles between antenna and transponder. Specifically, metal surfaces and water may interfere with signal transmission by reflecting or absorbing electromagnetic waves. It is generally not feasible to explicitly take all these parameters into account when modelling RFID sensors. Hähnel's solution to this issue was to consider only the position of the transponders in the horizontal plane. He created a stochastic sensor model by measuring detection rates for transponders in different configurations and averaging the results over all parameters not modelled. In order to compare our method with theirs, we also developed a probabilistic sensor model for our RFID system, visualized in Fig. 2.

For the snapshot-based approach, we do not require a specification of the sensor's detection field. Instead, each RFID inquiry is modelled as a random event which results in a succesful detection with a probability q. This probability is assumed to be fixed for a given position of the RFID antenna and the transponder in the environment. It is furthermore assumed that the value of q changes only little for small changes of the robot pose. This assumption was found to generally hold in experiments to assess sensor properties, although abrupt changes in detection rate do occur sometimes.

IV. Snapshot-Based Self-Localization

The proposed self-localization method is performed in the framework of a particle filter algorithm, also known as sequential Monte Carlo method [12]. In this algorithm, the variable of interest – here the pose of the robot – is represented by a set of particles $u^{(1)}, \ldots, u^{(n)}$, which evolve over time as the robot moves through the environment and performs RFID scans. Each particle consists of a hypothesis $\mathbf{r}$ of the robot's current pose and a weight w, giving a measure of the likelihood of the hypothesis. The pose vector $\mathbf{r}$ consists of the position of the robot in a global frame of reference and the robot's orientation. The evolution of the particles is carried out in three alternating steps, which are performed every time a new RFID snapshot $\mathbf{f}$ is taken:

1) *Resampling*: The new set of particles for time $t+1$ is obtained by drawing n times one particle from the set $u_t^{(1)}, \ldots, u_t^{(n)}$, choosing particle i with probability $w_t^{(i)}$.
2) *Prediction*: The change of the robot pose since the last RFID scan is predicted by drawing a new pose hypothesis for each particle from the distribution $p(\mathbf{r}_{t+1}|\mathbf{r}_t)$. This distribution can be derived from a motion model of the robot based on odometry data.
3) *Correction*: The particle weights are updated according to

$$w_{t+1}^{(i)} = \frac{p(\mathbf{f}_{t+1}|\mathbf{r}_{t+1}^{(i)})}{\sum_{j=1}^{n} p(\mathbf{f}_{t+1}|\mathbf{r}_{t+1}^{(j)})}. \tag{1}$$

By these operations, the particles converge towards a discrete representation of the probability distribution of the robot's pose, which can be estimated as the weighted sum of the particle poses.

The crucial element in this method is the definition of the likelihood function $p(\mathbf{f}_t|\mathbf{r}_t)$, which is used to update the particle weights in the correction step. The function presented below first computes an estimate $\hat{q}$ of the detection probability for each tag from the reference snapshots. Then it determines the probability of the given scan based on this estimate. Each reference snapshot allows for the estimation of the detection probabilities at the position it was taken at via Bayes' formula, yielding

$$\hat{q}_l(f_l) = \int_0^1 q_l p(q_l|f_l) dq_l \tag{2}$$

for a single tag l, with

$$p(q_l|f_l) = \frac{p(f_l|q_l)p(q_l)}{\int_0^1 p(f_l|q_l')p(q_l')dq_l'} \tag{3}$$

and the conditional probability $p(f_l|q_l)$ following the binomial distribution

$$p(f_l|q_l) = \binom{N_{max}}{f_l} q_l^{f_l}(1-q_l)^{N_{max}-f_l}. \tag{4}$$

Furthermore, $p(q_l)$ is the a-priori distribution of the detection probability q_l, which can be derived from the known properties of the RFID sensor: In the major part of the environment, the detection of a specific tag will be almost impossible (because it is out of sensor range or not in the direction in which the RFID antennas are pointing). Consequently, the detection probability will be close to zero. Detection probabilities considerably higher than zero are assumed to occur with approximately equal frequency, so the distribution $p(q_l)$ is modelled by a step function with a high value close to zero and a constant low value in the rest of the interval $[0, 1]$.

A reliable estimate of the detection probabilities for an arbitrary antenna pose $\mathbf{a}$ can now be calculated as the weighted mean of the estimates obtained from reference snapshots $\mathbf{f}^{(1)}, \ldots, \mathbf{f}^{(r)}$ taken in the vicinity of $\mathbf{a}$,

$$\hat{\mathbf{q}}(\mathbf{a}) = \alpha_1 \hat{\mathbf{q}}(\mathbf{f}^{(1)}) + \ldots + \alpha_r \hat{\mathbf{q}}(\mathbf{f}^{(r)}) + \beta \hat{\mathbf{q}}_\mathbf{0} \tag{5}$$

with $\sum_{j=1}^{r} \alpha_j + \beta = 1$ and $\hat{\mathbf{q}} = (q_1, \ldots, q_k)^T$. Here, $\hat{\mathbf{q}}_0$ is an estimate of the detection probabilities in the absence of reference scans. This vector with equal entries $\hat{q}_0$ can be obtained from the a-priori distribution $p(q)$ via

$$\hat{q}_0 = \int_0^1 p(q)\, q\, dq. \tag{6}$$

The weights α_j are calculated from the distance between the antenna pose and the pose at which the snapshot was taken by a Gauss function. Note that the metric used to determine this distance must also take the orientations of the antennas into account. The weight β of the a-priori estimate is 1 if no reference scans were taken in the vicinity of the pose under consideration, and should decrease the more reference scans are available and the closer they are to $\mathbf{a}$. This can be achieved by first setting β to a small constant value and then normalizing it when the (non-normalized) weights of the snapshots are known.

Finally, the estimate $\hat{\mathbf{q}}(\mathbf{a})$ can be used to compute the likelihood of a robot pose. To this end, the probabilities of the observed detection frequencies are determined by inserting the estimated detection probabilities $\hat{q}_l(\mathbf{a})$ of each tag into Eq. 4. Under the assumption that the measurements of the single tags are independent, the probability of the whole snapshot $\mathbf{f}$ is

$$p(\mathbf{f}|\mathbf{a}) = \prod_{l=1}^{k} p(f(l)|\hat{q}_l(\mathbf{a})). \tag{7}$$

From this equation, the likelihood function required for the particle filter algorithm can be obtained by determining the antenna pose $\mathbf{a}$ from the robot pose $\mathbf{r}$ of each particle. In our RFID system, the snapshots of the left and right antenna pairs are taken simultaneously, and both are used in a single correction step. The resulting likelihood function is

$$p(\mathbf{f}_l, \mathbf{f}_r|\mathbf{r}) = p(\mathbf{f}_l|\mathbf{a}_l(\mathbf{r}))p(\mathbf{f}_r|\mathbf{a}_r(\mathbf{r})), \tag{8}$$

where $\mathbf{a}_l(\mathbf{r})$ and $\mathbf{a}_r(\mathbf{r})$ denote the poses of the left and right antenna pair if the robot is at pose $\mathbf{r}$, and $\mathbf{f}_l$ and $\mathbf{f}_r$ are the corresponding snapshots.

V. Experimental Results

In order to evaluate the performance of our algorithm, we measured the accuracy of the pose estimate under different conditions. Experiments were conducted with an RWI (iRobot) B21 robot in our institute's robot laboratory and adjacent corridors. The experiments described in Subsections V-A and V-B, which assess the influence of the extent of the training phase and of internal parameters of the algorithm, were conducted in the robot lab only, with a free area of approximately 50 m^2. For the experiment described in Subsection V-C, where the influence of transponder placement and density is investigated, the larger environment with a total free area of approximately 195 m^2 was used. During the training phase, the position of the robot was determined via odometry only. We made sure that the deviation from the true position did not exceed 20 cm after each trial. The results presented in this section are averaged over 3-5 learning runs each, with 5 different starting positions for the self-localization after the training phase. We executed the algorithm by Hähnel et al. with identical RFID and odometry data to justify a direct comparison of the two approaches.

A. Influence of the Density of Reference Snapshots

In the first experiment, we investigated the density of reference snapshots required to achieve an accurate pose estimate. The experiment was conducted in the robot lab with 28 to 80 transponders attached to walls and to furniture in different trials. In the first set of trials, we took a total number of 1000 snapshots during the training phase. This corresponds to a distance of approximately 50 m, travelled at a speed of 0.2 m/s with two snapshots for each antenna pair taken per second. In the other sets of trials, we extended the learning runs to retrieve 2000 and 3000 reference snapshots, respectively. The results are shown in Fig. 3. The mean absolute estimation error for 1000 snapshots was about 0.6 m after few steps of the particle filter and then remained on this level. For 2000 snapshots, the error was reduced to below 0.4 m. An additional increase in the number of snapshots brought no clear improvement.

To check whether the reduced estimation error was an effect of the higher average density of snapshots or of a better coverage of the area due to the longer learning run, an additional set of self-localization trials was performed. For these trials, 1000 reference snapshots were chosen randomly from the 3000 snapshots of the longest learning runs. Estimation errors were comparable to the original trials with 1000 snapshots taken in a shorter learning run. This indicates that the average snapshot density is indeed the crucial factor for the accuracy of the method.

B. Influence of the Number of Particles

In the next experiment, we investigated the influence of the number of particles on the estimation error for both the snapshot-based algorithm and the algorithm proposed by Hähnel. The same sensory data were used as in the trials above with 2000 reference snapshots. The mean errors of the pose estimates using a particle filter with 50, 100, and 200

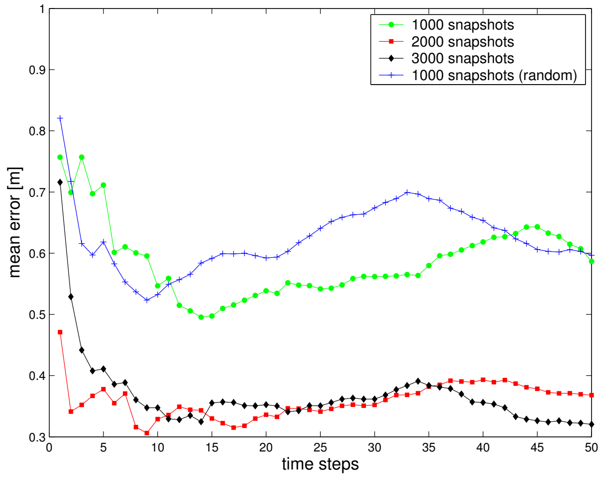

Fig. 3. The mean absolute localization error over time, depending on the number of snapshots taken during the training phase for an area of approximately 50 m^2.

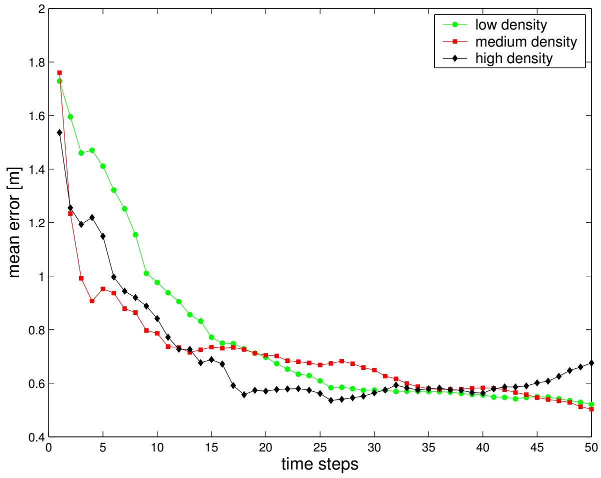

Fig. 5. Impact of the density of RFID transponders on the localization accuracy when the method by Hähnel et al. is used.

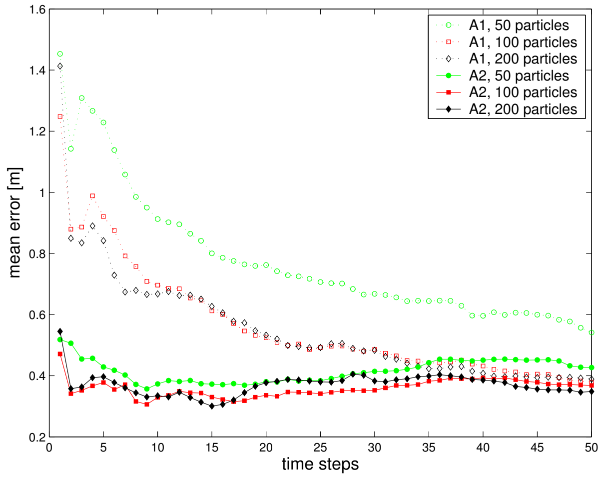

Fig. 4. Influence of the number of particles on the localization error over time. The algorithm used by Hähnel et al. is denoted as *A1* (dotted curves), our method as *A2* (solid curves). Overall, the snapshot-based algorithm converges faster and provides stable pose estimates after few time steps already.

particles are presented in Fig. 4. A number of 100 particles are sufficient in both algorithms to achieve optimal results. In the snapshot-based algorithm, close to optimal results can be observed with only 50 particles. Note that the results for our implementation of Hähnel's algorithm are in good accordance with the ones published in [5], despite the differences in the RFID systems used. The comparison of the two algorithms shows that estimation errors after 50 steps are almost equal at about 0.4 m. However, the snapshot-based approach achieves this accuracy after only a few steps, while Hähnel's algorithm takes much longer.

C. Influence of the Arrangement of Transponders

The influence of the placement of transponders and their density in the environment was examined in the final experiment. In one series of trials, transponders were placed regularly spaced approximately every two meters on the walls at the height of the robot's RFID antennas. This setup was similar to the one used by Hähnel. Two other settings were used in which more transponders were placed in the environment in a less systematic fashion (different heights and orientations, attached to different objects). One of these featured a medium transponder density, the other one featured a high density and was restricted to the robot lab. The mean absolute errors for the self-localization in these settings are shown in Fig. 5 and 6. For Hähnel's algorithm, density and placement of the transponders have little impact on the estimation error, although an accurate pose estimate is achieved slightly faster for higher transponder densities. The accuracy of the snapshot-based approach is reduced considerably in case of the lowest transponder density. Closer inspection of the single trials revealed that the self-localization yielded poor results only in one corridor. Here, only very few transponders were visible at the same time, and the set of visible transponders remained unchanged over a large range of positions and orientations. Under these conditions, the snapshots provided only very little information to discriminate between different poses. If the corresponding trials are removed from the dataset, the estimation error for the lowest density is virtually equal to the error in the other settings.

D. Run-Time Measurements

During the experiments, we recorded the time that was required to perform one step of the particle filter cycle. All experiments were run on the on-board 2 GHz Pentium processor. Under typical conditions (100 particles, medium transponder density), it took 7.2 ms per step on average for the snapshot-based algorithm and 7.6 ms for the algorithm by Hähnel et al. Thus, both approaches can easily be used in real-time applications.

VI. Conclusion

A. Summary

In this paper, we presented a novel algorithm for the self-localization of a mobile robot via RFID. Inspired by vision-

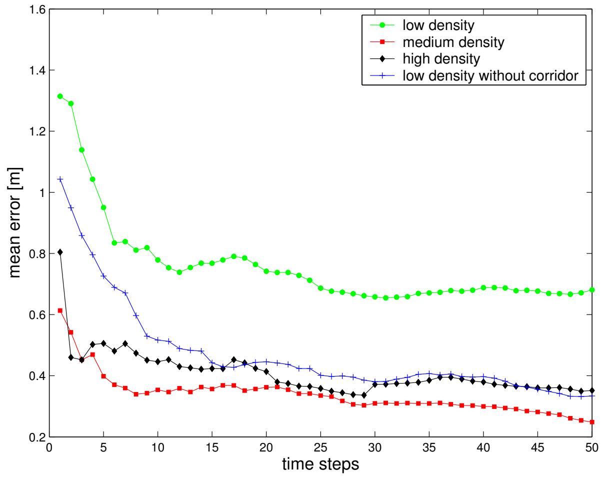

Fig. 6. Impact of the density of RFID transponders on the localization accuracy when our snapshot-based method is used. For the lowest density, results are additionally plotted after removing trials that were performed under adverse conditions (narrow corridor with very few transponders visible).

based approaches, the robot first learns RFID snapshots at known positions in the environment during a training phase. These feature vectors are comprised of an accumulated list of recently detected tags along with their detection counts. After the training, during normal operation of the robot, we match current snapshots with the memorized features. To achieve robust pose estimation despite the uncertainty of the raw scan results, the self-localization is performed in the framework of a particle filter.

Under most conditions, the algorithm yields pose estimates with similar or higher accuracy than a comparable approach by Hähnel et al., with a mean estimation error of approx. 0.4 m. In addition, our algorithm converges considerably faster to the approximate robot pose. A stable pose estimation is usually gained after few steps of the particle filter. However, the approach presented in this paper has some drawbacks: The training phase may be quite time-consuming, since a large number of snapshots are needed to cover extensive environments. Accurate self-localization is only possible in the very areas that are covered by reference snapshots, whereas algorithms which rely on (estimated) transponder positions offer a certain amount of generalization. Moreover, in situations where only very few transponders can be detected by the robot, the pose estimation is rather unreliable. On the other hand, the snapshot-based approach is advantageous in so far that it does not require an explicit sensor model.

In comparison to other sensor systems like vision and laser scanners, the accuracy of loalization that can be achieved with RFID systems is quite limited. The advantage of using RFID is that a rough pose estimate can be obtained without ambiguities due to the unique IDs of the transponders. This makes these systems a favorable choice for sensor fusion approaches.

B. Future Work

For the future, we plan to research into exploration strategies which automate the time-consuming training phase. Additionally, we would like to integrate the possibility to revise the database of learned features on-line, i.e. during normal operation. We are further going to fuse the RFID data with other types of sensors.

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